titanic-assignment

July 27, 2024

[1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import numpy as np
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
%matplotlib inline
# magic command
import seaborn as sns
```

[2]:
```
import os
```

[3]:
```
os.getcwd()
```

[3]:
```
'C:\\Users\\abhil'
```

[4]:
```
df = pd.read_csv('titanic_train.csv')
```

[5]:
```
df.head()
```

[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th…	female	38.0	1					
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0					
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1					
4	5	0	3	Allen, Mr. William Henry	male	35.0	0					

```
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[6]:
```
df.tail()
```

[6]:
```
     PassengerId  Survived  Pclass                                      Name  \
886          887         0       2                     Montvila, Rev. Juozas
887          888         1       1              Graham, Miss. Margaret Edith
888          889         0       3  Johnston, Miss. Catherine Helen "Carrie"
889          890         1       1                     Behr, Mr. Karl Howell
890          891         0       3                       Dooley, Mr. Patrick

        Sex   Age  SibSp  Parch      Ticket   Fare Cabin Embarked
886    male  27.0      0      0      211536  13.00   NaN        S
887  female  19.0      0      0      112053  30.00   B42        S
888  female   NaN      1      2  W./C. 6607  23.45   NaN        S
889    male  26.0      0      0      111369  30.00  C148        C
890    male  32.0      0      0      370376   7.75   NaN        Q
```

[7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[8]:
```
df.describe()
```

[8]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
```

```
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[9]:
```
df.describe(include="O")# object
```

[9]:
```
                          Name   Sex  Ticket    Cabin Embarked
count                      891   891     891      204      889
unique                     891     2     681      147        3
top     Braund, Mr. Owen Harris  male  347082  B96 B98        S
freq                         1   577       7        4      644
```

[10]:
```
df.describe(percentiles=[0.10,0.20,0.50,0.90])
```

[10]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
10%      90.000000    0.000000    1.000000   14.000000    0.000000
20%     179.000000    0.000000    1.000000   19.000000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
90%     802.000000    1.000000    3.000000   50.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
10%      0.000000    7.550000
20%      0.000000    7.854200
50%      0.000000   14.454200
```

```
90%       2.000000   77.958300
max       6.000000  512.329200
```

[11]:
```
df.isnull()
```

[11]:
```
     PassengerId  Survived  Pclass   Name    Sex    Age  SibSp  Parch  Ticket  \
0          False     False   False  False  False  False  False  False   False
1          False     False   False  False  False  False  False  False   False
2          False     False   False  False  False  False  False  False   False
3          False     False   False  False  False  False  False  False   False
4          False     False   False  False  False  False  False  False   False
..           …         …     …      …      …      …      …      …
886        False     False   False  False  False  False  False  False   False
887        False     False   False  False  False  False  False  False   False
888        False     False   False  False  False   True  False  False   False
889        False     False   False  False  False  False  False  False   False
890        False     False   False  False  False  False  False  False   False

      Fare  Cabin  Embarked
0    False   True     False
1    False  False     False
2    False   True     False
3    False  False     False
4    False   True     False
..     …     …        …
886  False   True     False
887  False  False     False
888  False   True     False
889  False  False     False
890  False   True     False

[891 rows x 12 columns]
```

[12]:
```
df.isnull().sum()
```

[12]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
```

```
dtype: int64
```

[13]:
```
df.isnull().sum().sum()
```

[13]:
```
866
```

[14]:
```
df.isnull().any()
```

[14]:
```
PassengerId    False
Survived       False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
Parch          False
Ticket         False
Fare           False
Cabin           True
Embarked        True
dtype: bool
```

[15]:
```
len(df)
```

[15]:
```
891
```

[16]:
```
df1=df.copy()
```

[17]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
```

```
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[18]:
```
# percentage of missing value
df.isnull().sum()/len(df)*100
```

[18]:
```
PassengerId     0.000000
Survived        0.000000
Pclass          0.000000
Name            0.000000
Sex             0.000000
Age            19.865320
SibSp           0.000000
Parch           0.000000
Ticket          0.000000
Fare            0.000000
Cabin          77.104377
Embarked        0.224467
dtype: float64
```

[19]:
```
df1=df.copy()
```

[20]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[21]:
```
df1.drop(['Name', 'Ticket', 'Cabin'], axis=1, inplace=True)
```

[22]:
```
df1["Age"]=df1["Age"].fillna(df1["Age"].mean())
```

[23]:
```
df1["Embarked"] = df1["Embarked"].fillna(df1["Embarked"].mode()[0])
```

[24]:
```
df1.info()
```

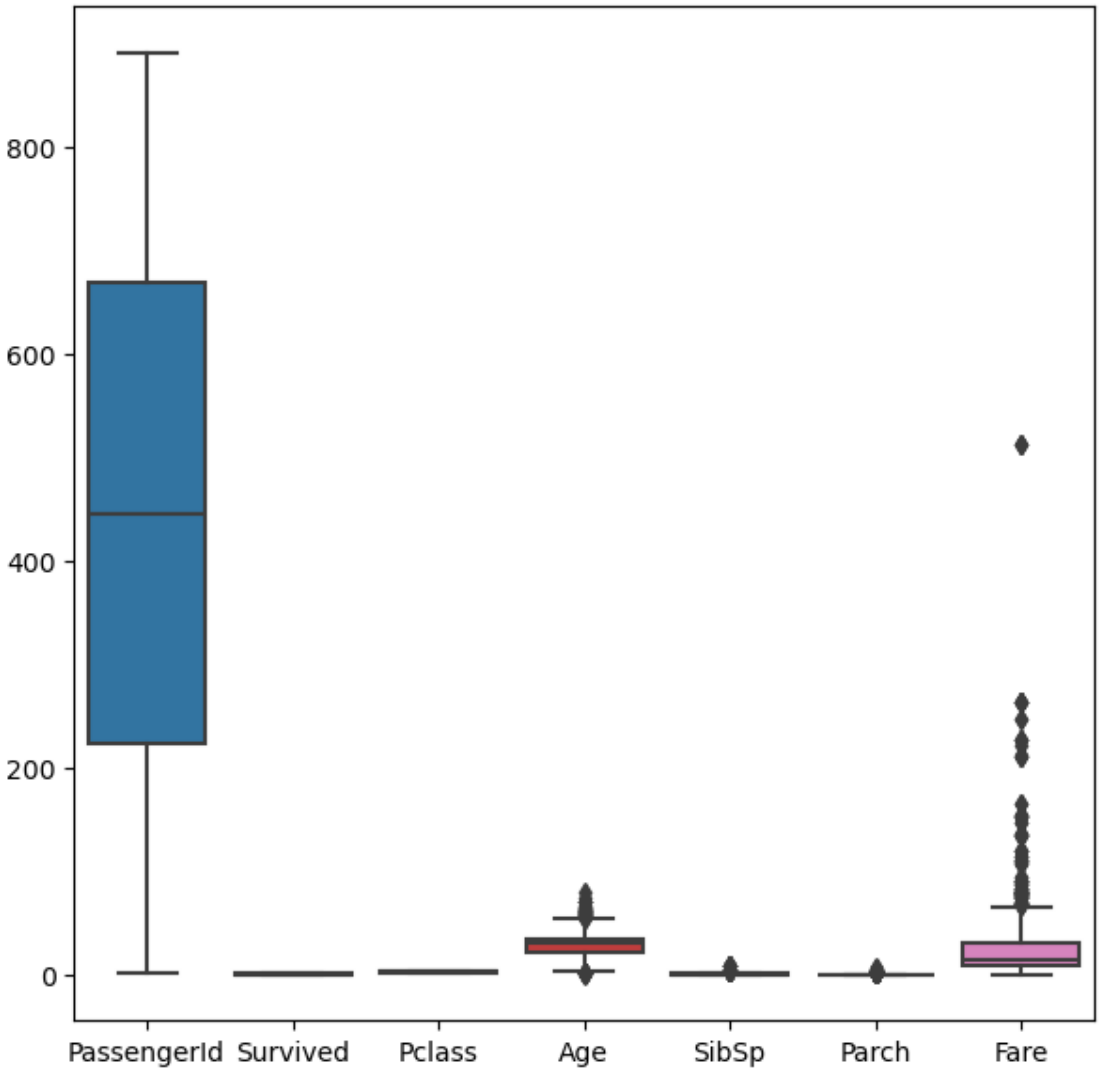
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Sex          891 non-null    object 
 4   Age          891 non-null    float64
 5   SibSp        891 non-null    int64  
 6   Parch        891 non-null    int64  
 7   Fare         891 non-null    float64
 8   Embarked     891 non-null    object 
dtypes: float64(2), int64(5), object(2)
memory usage: 62.8+ KB
```

[25]:
```
df1.isnull().sum().sum()
```

[25]:
```
0
```

[26]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df1)
```

[26]:
```
<Axes: >
```



[27]:
```
df1.describe()
```

[27]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	13.002015	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	29.699118	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

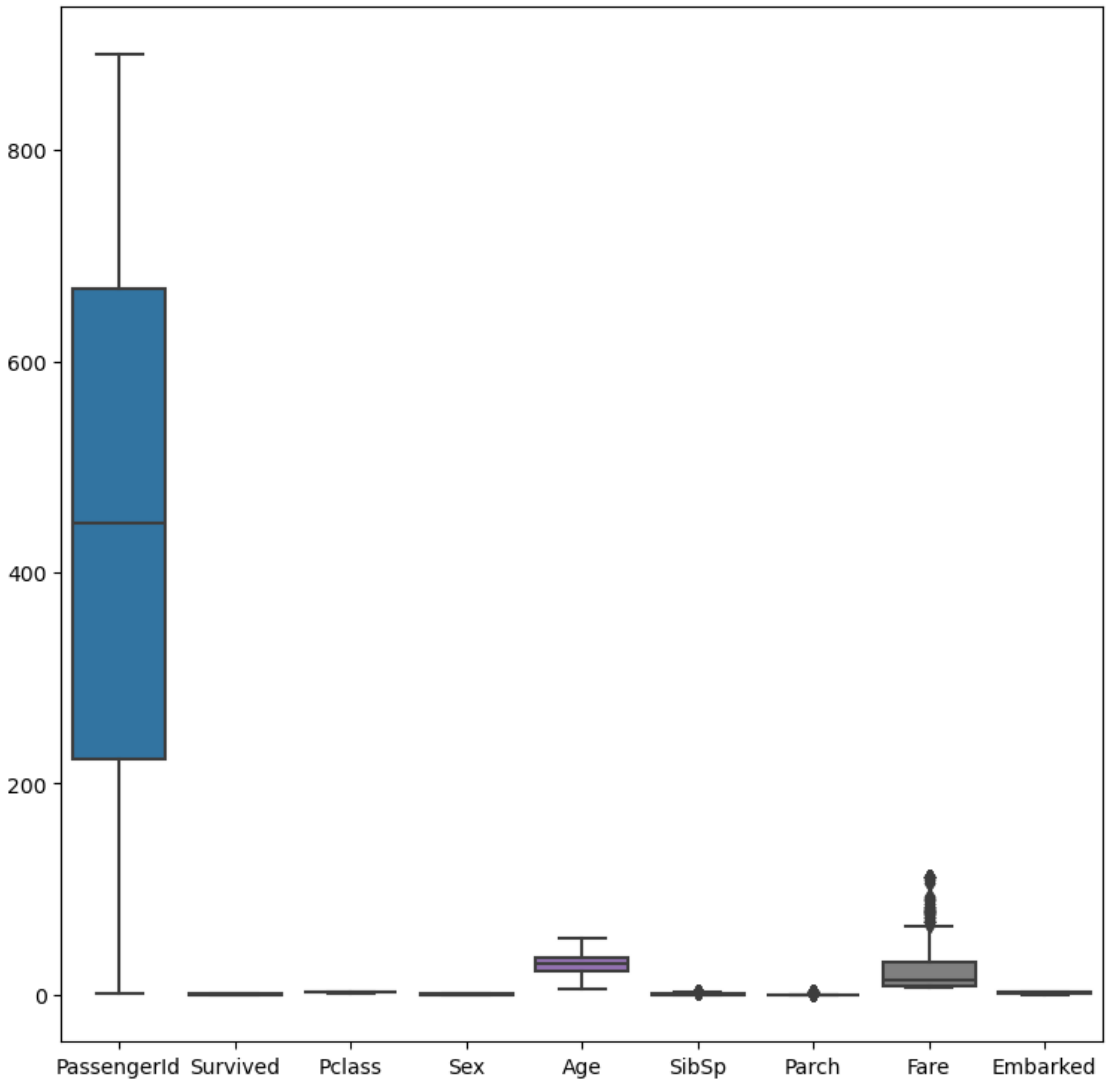
```
mean      0.381594   32.204208
std       0.806057   49.693429
min       0.000000    0.000000
25%       0.000000    7.910400
50%       0.000000   14.454200
75%       0.000000   31.000000
max       6.000000  512.329200
```

[28]:
```
df1['Sex'] = df1['Sex'].map({'male': 0, 'female': 1})
df1['Embarked'] = df1['Embarked'].map({'C': 0, 'Q': 1, 'S': 2})
```

[29]:
```
def cap_outliers(series, lower_percentile=0.05, upper_percentile=0.95):
    lower_bound = series.quantile(lower_percentile)
    upper_bound = series.quantile(upper_percentile)
    return np.clip(series, lower_bound, upper_bound)
numerical_columns = ['Age', 'SibSp', 'Parch', 'Fare']
for column in numerical_columns:
    df1[column] = cap_outliers(df1[column])
```

[30]:
```
plt.figure(figsize=(9,9))
sns.boxplot(data=df1)
```

[30]:
```
<Axes: >
```

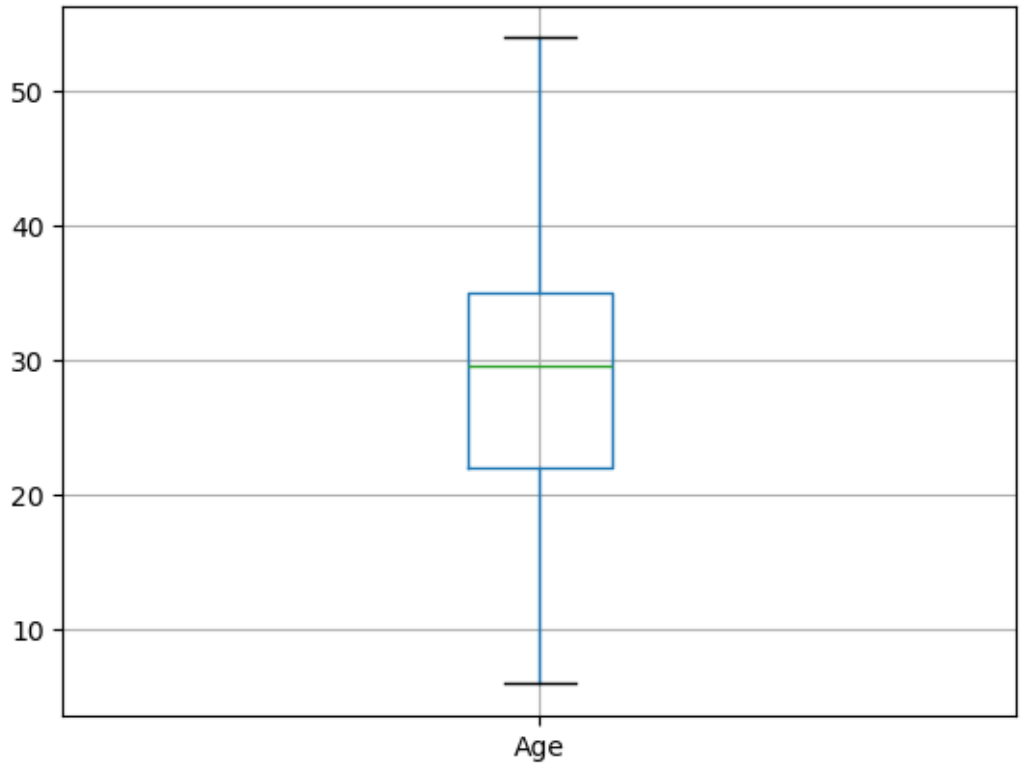


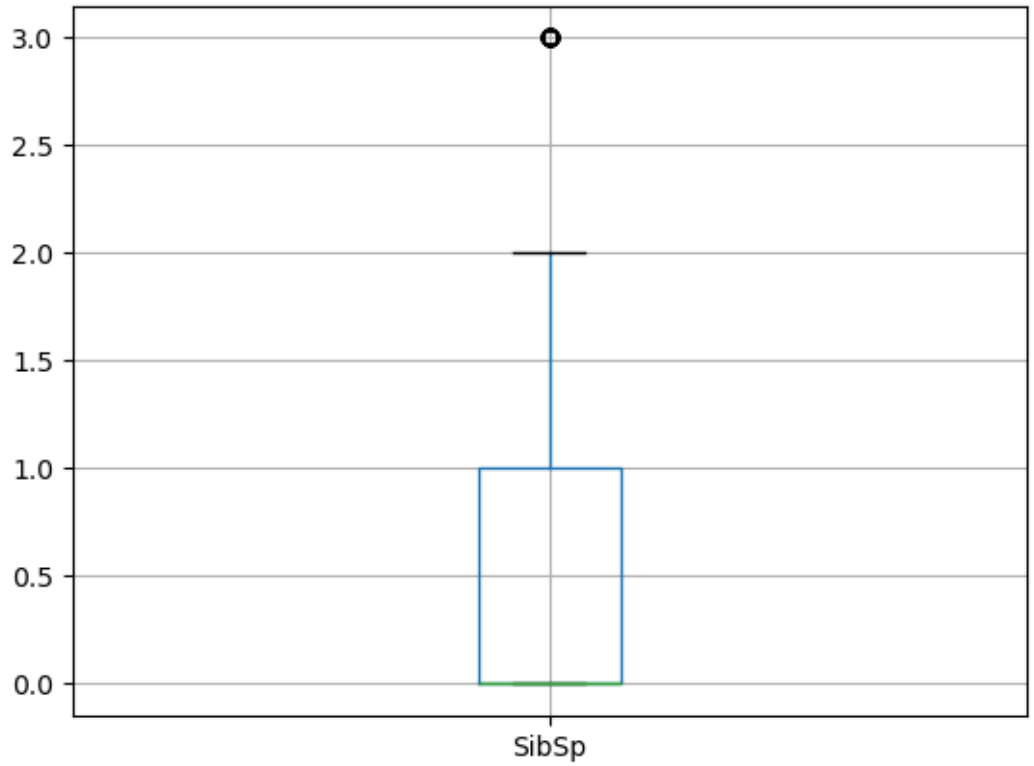
[31]:
```
df1.info()
```

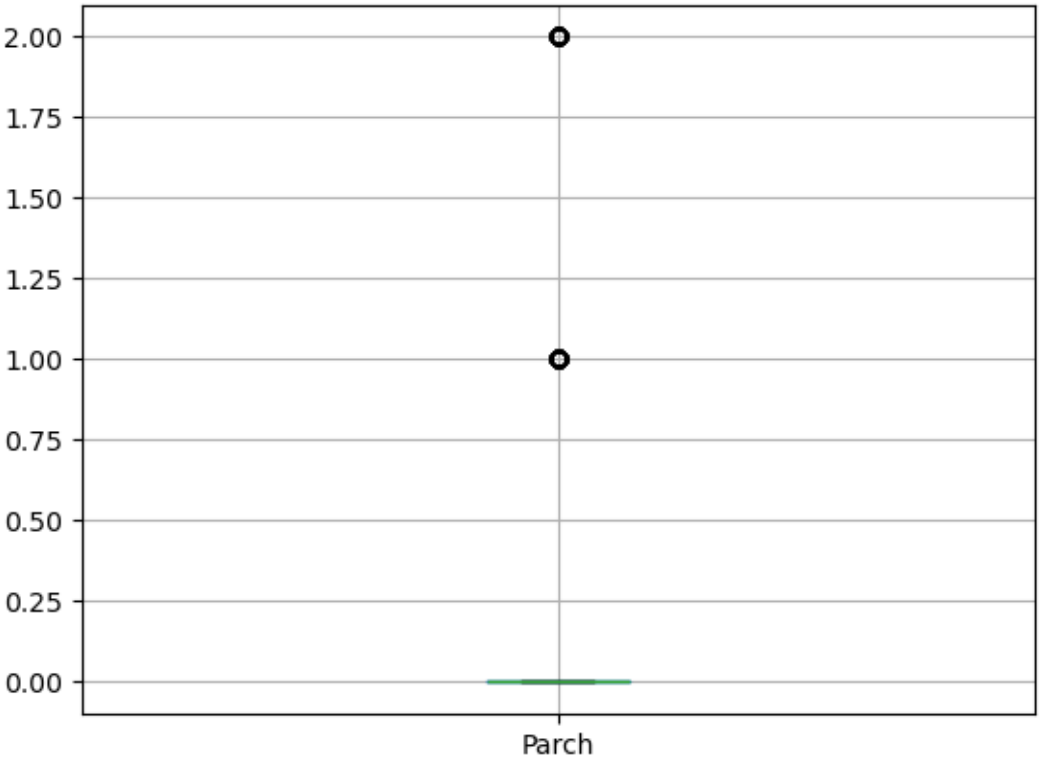
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Sex          891 non-null    int64
 4   Age          891 non-null    float64
 5   SibSp        891 non-null    int64
 6   Parch        891 non-null    int64
```

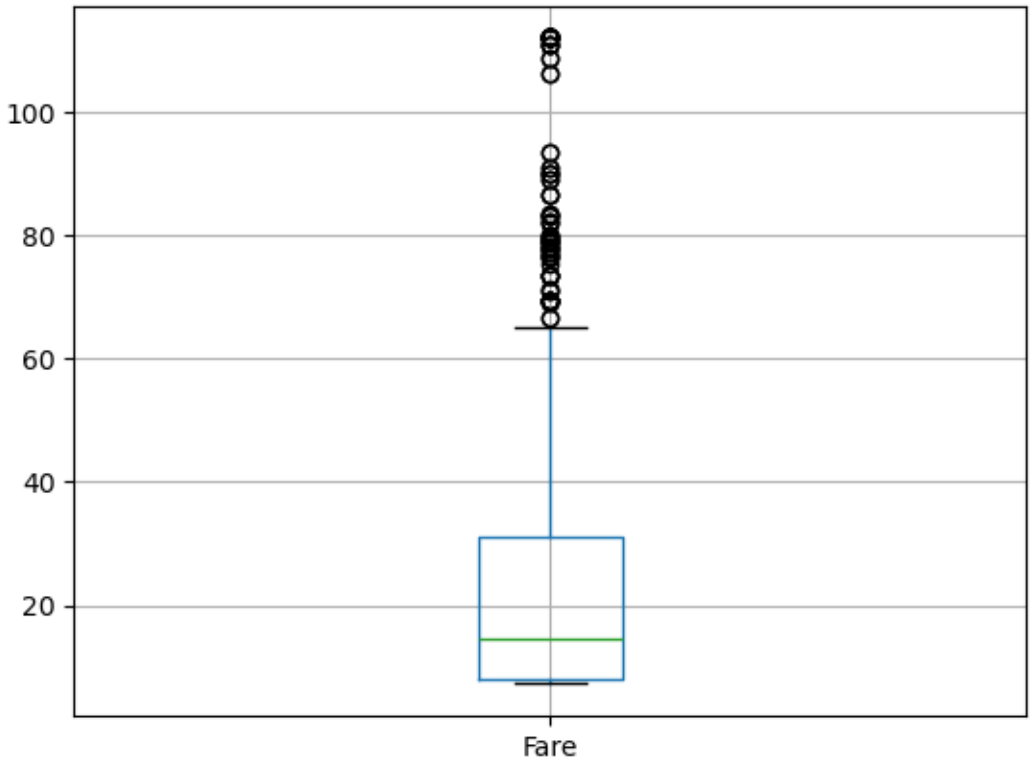
```
 7   Fare         891 non-null    float64
 8   Embarked     891 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 62.8 KB
```

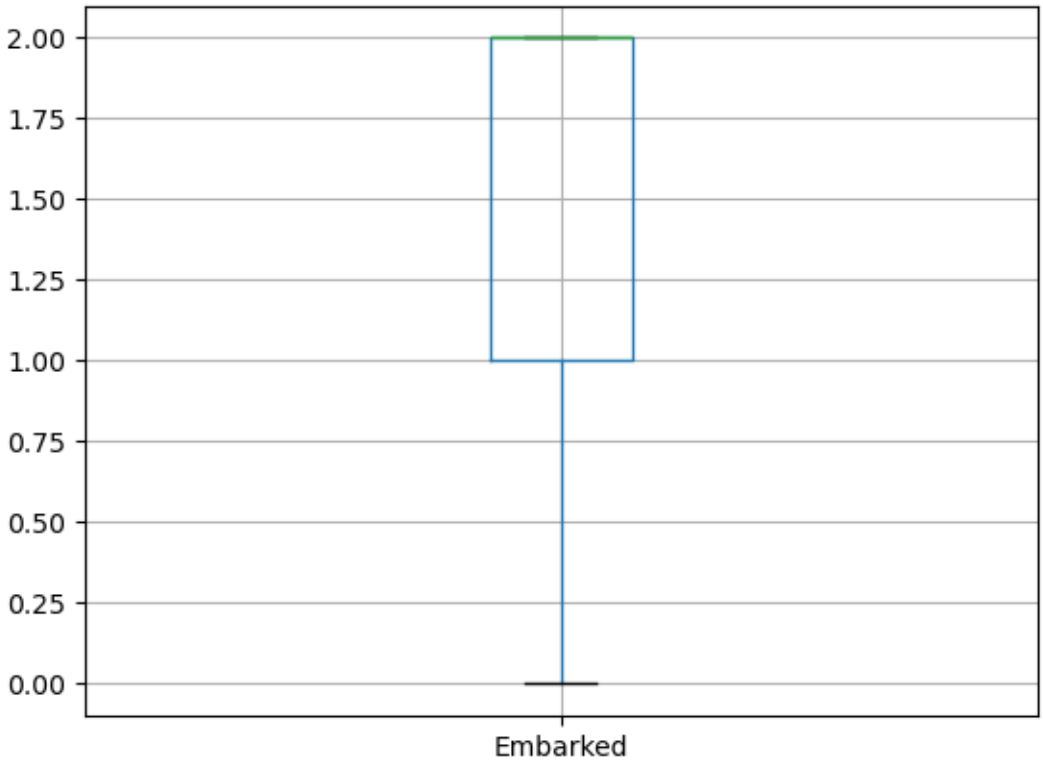
[32]:
```
df100=df1[["Age","SibSp","Parch","Fare", "Embarked"]]
for column in df100:
    plt.figure()
    df100.boxplot([column])
```



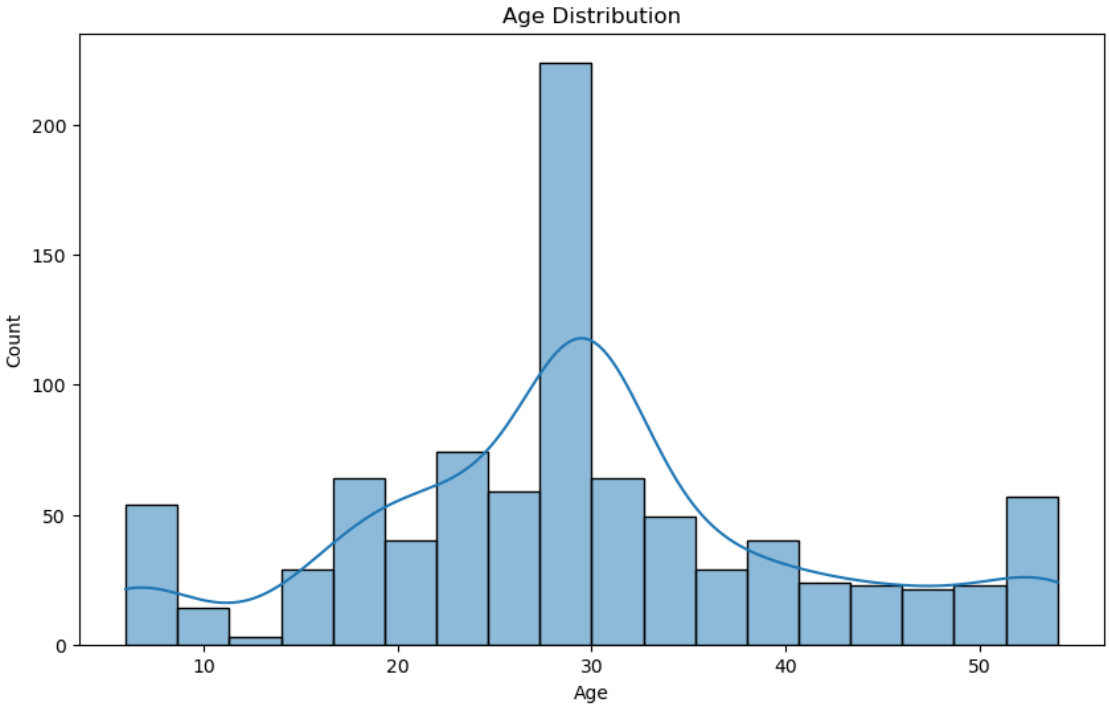

3.0
2.5
2.0
1.5
1.0
0.5
0.0
SibSp


2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Parch

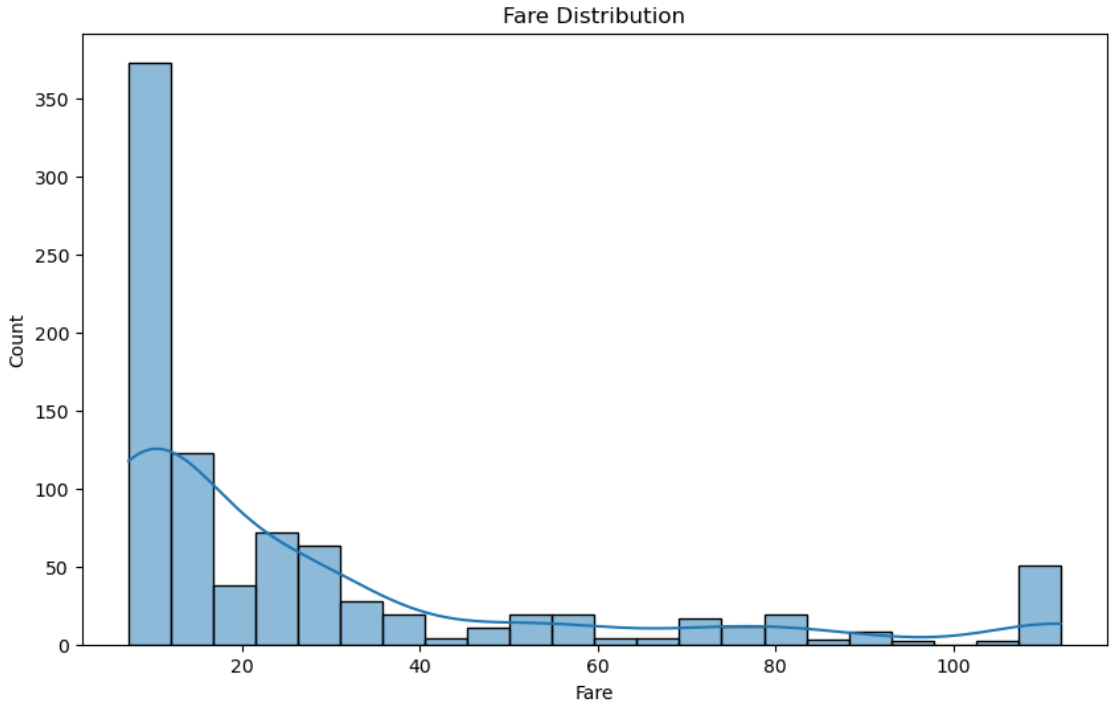

100
80
60
40
20
Fare



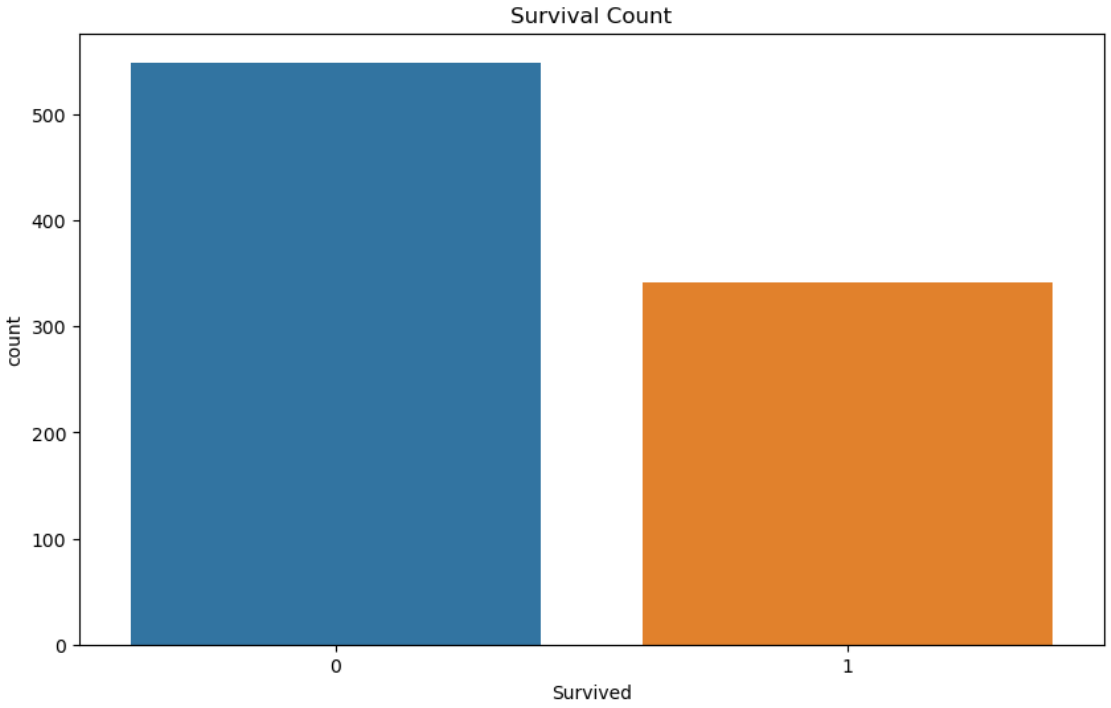
[33]:
```
plt.figure(figsize=(10, 6))
sns.histplot(df1['Age'], kde=True)
plt.title('Age Distribution')
plt.show()
```



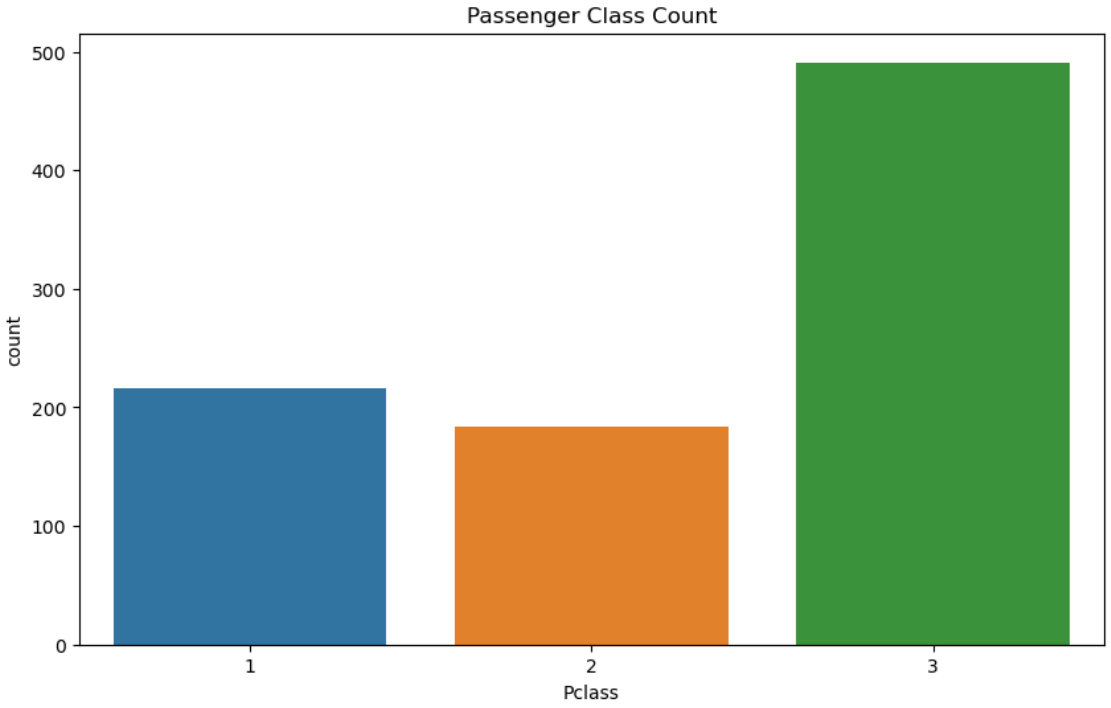
[34]:
```
plt.figure(figsize=(10, 6))
sns.histplot(df1['Fare'], kde=True)
plt.title('Fare Distribution')
plt.show()
```



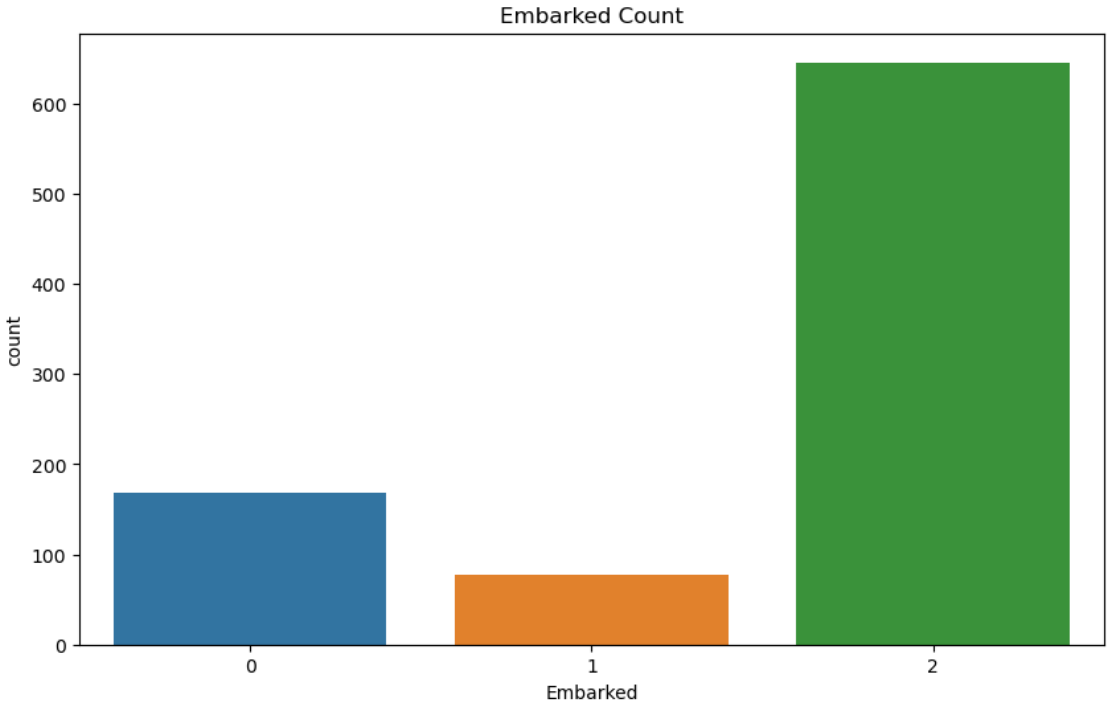
[35]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Survived', data=df1)
plt.title('Survival Count')
plt.show()
```



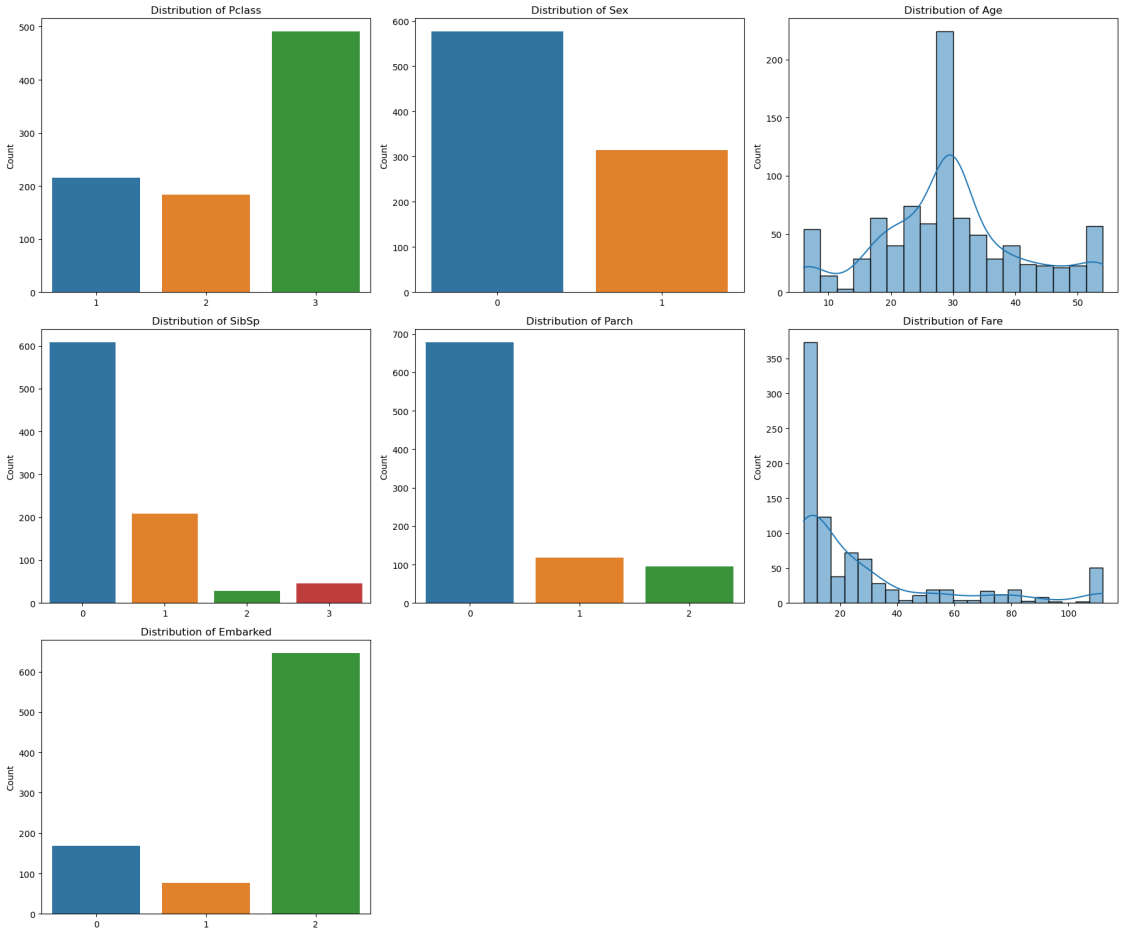
[36]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Pclass', data=df1)
plt.title('Passenger Class Count')
plt.show()
```



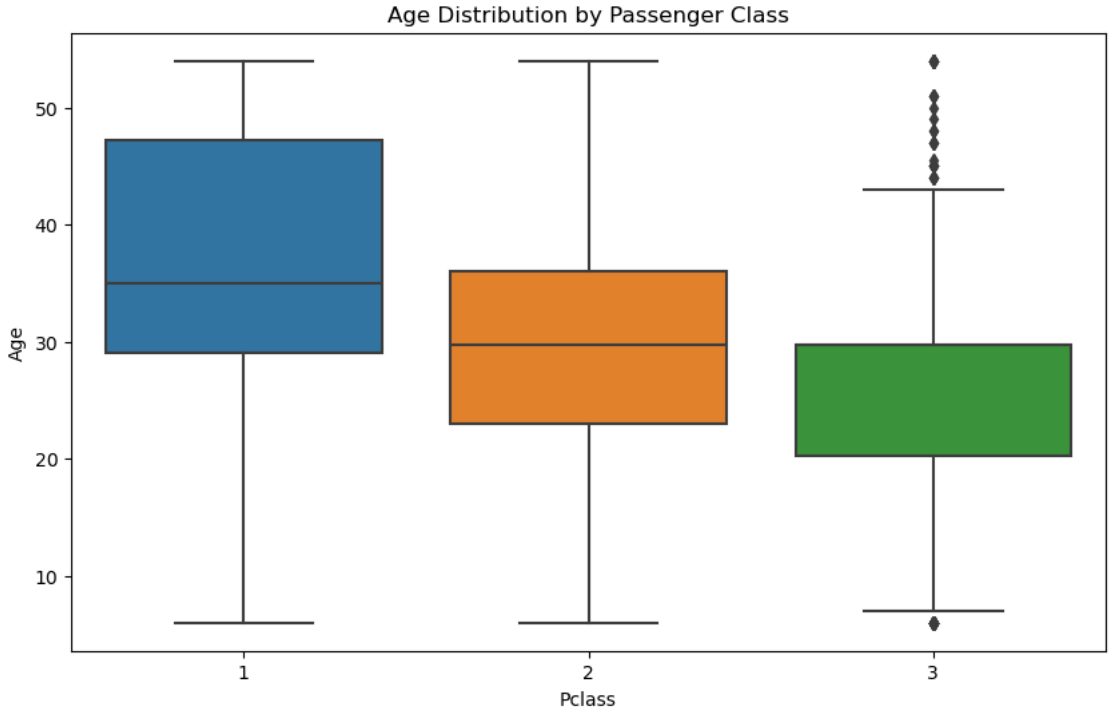
[37]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Embarked', data=df1)
plt.title('Embarked Count')
plt.show()
```



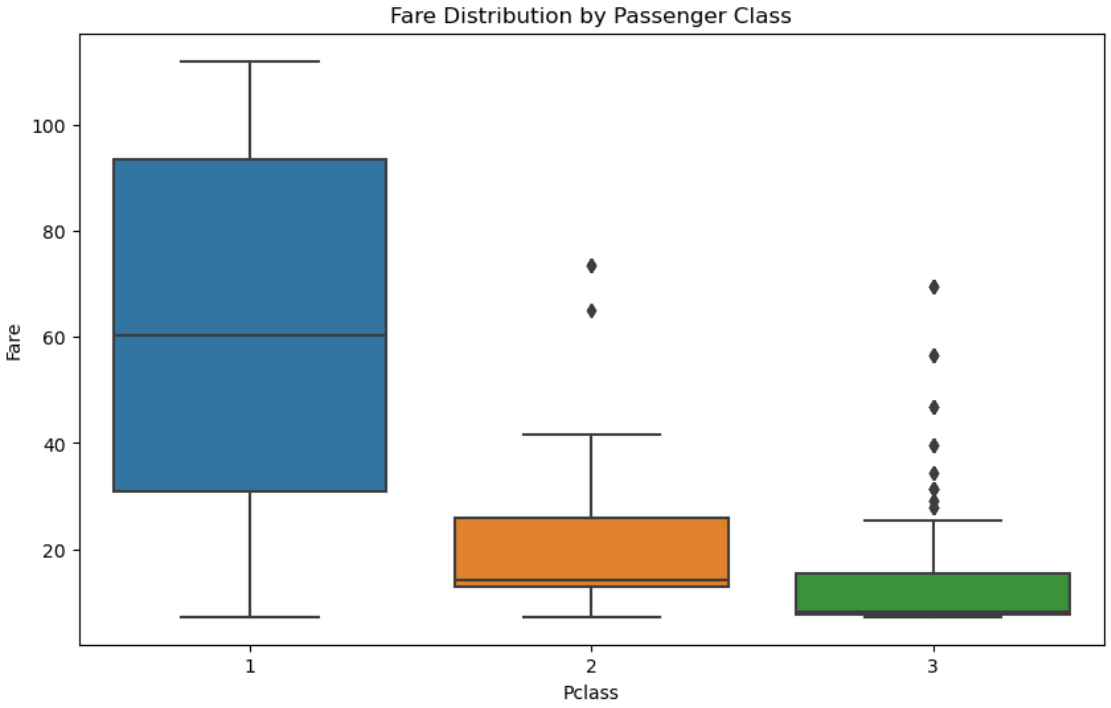
[38]:
```
features = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked']

fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(18, 15))

axes = axes.flatten()

for i, feature in enumerate(features):
    if df1[feature].dtype == 'object' or len(df1[feature].unique()) < 10:
        sns.countplot(x=feature, data=df1, ax=axes[i])
    else:
        sns.histplot(df1[feature], ax=axes[i], kde=True)
    axes[i].set_title(f'Distribution of {feature}')
    axes[i].set_xlabel('')
    axes[i].set_ylabel('Count')

for j in range(len(features), len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```



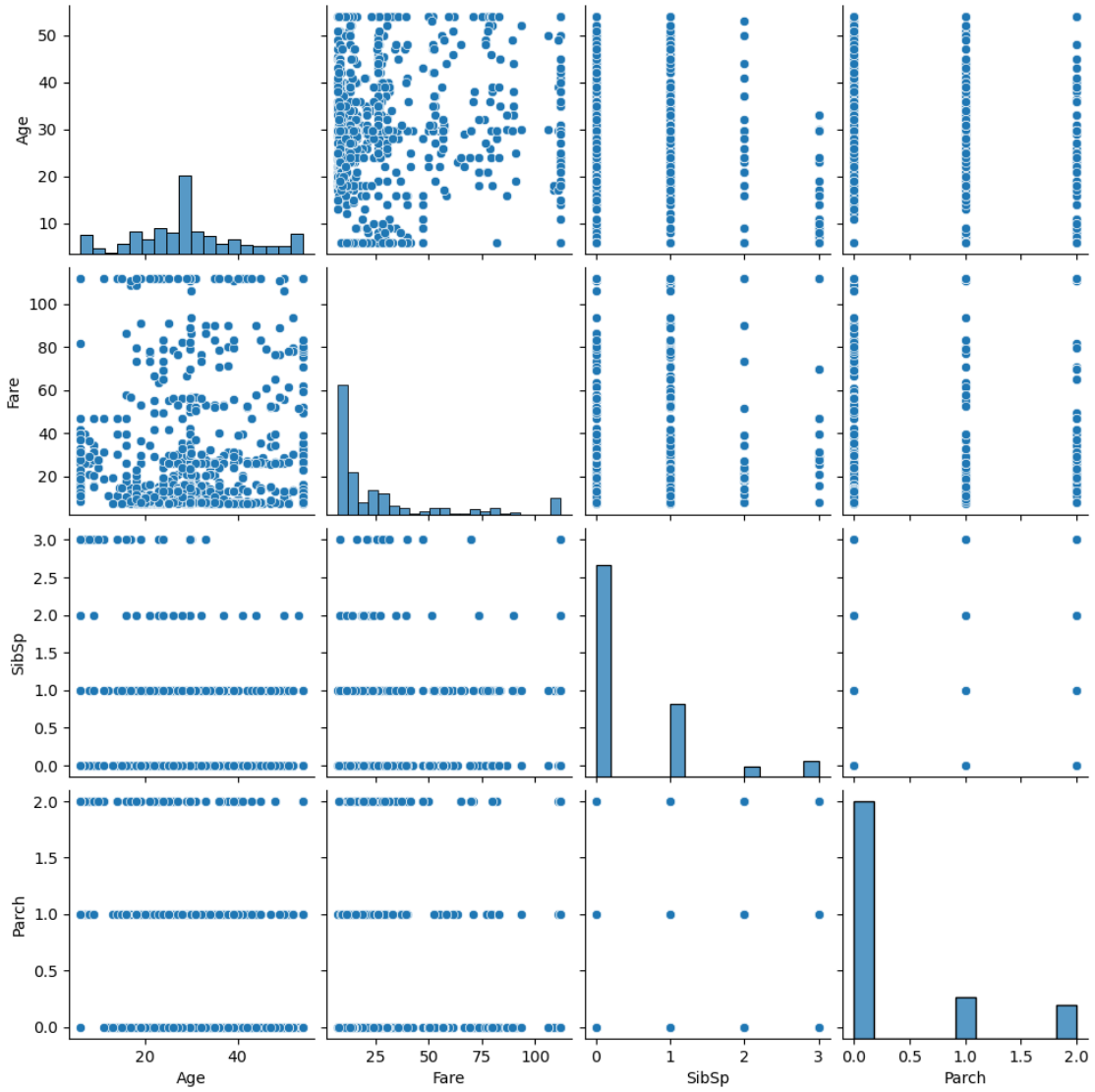
[39]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Pclass', y='Age', data=df1)
plt.title('Age Distribution by Passenger Class')
plt.show()
```



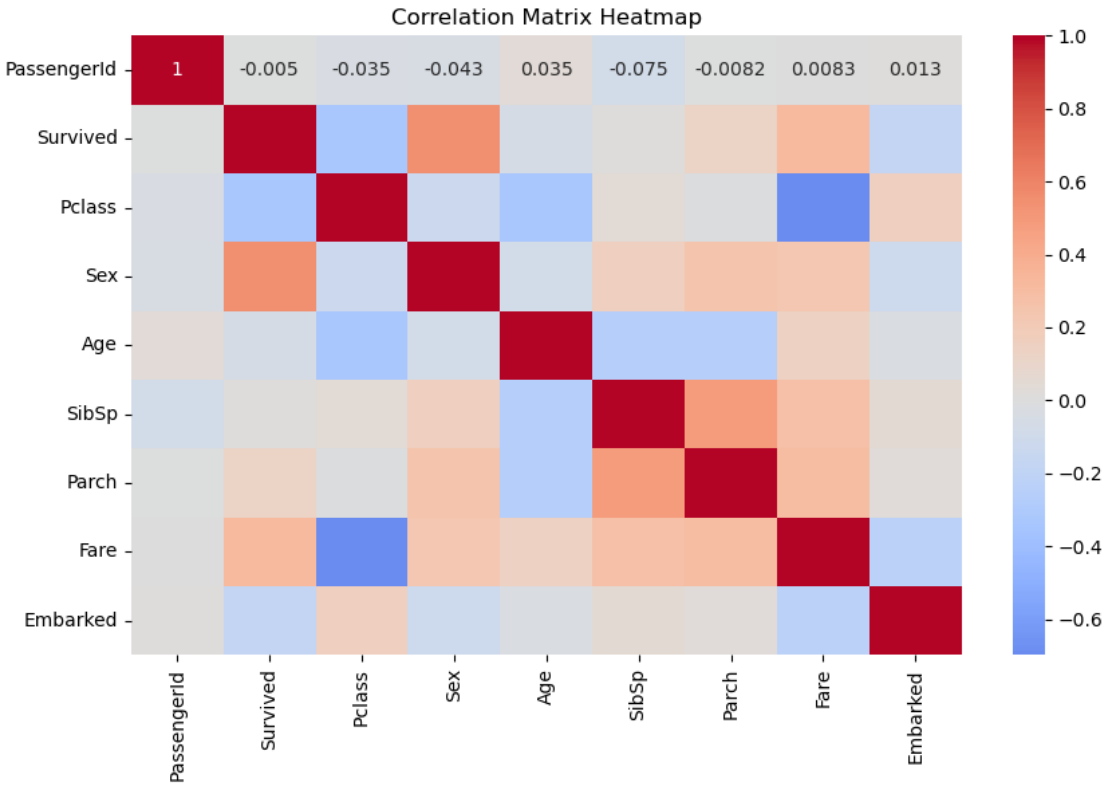
[40]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Pclass', y='Fare', data=df1)
plt.title('Fare Distribution by Passenger Class')
plt.show()
```



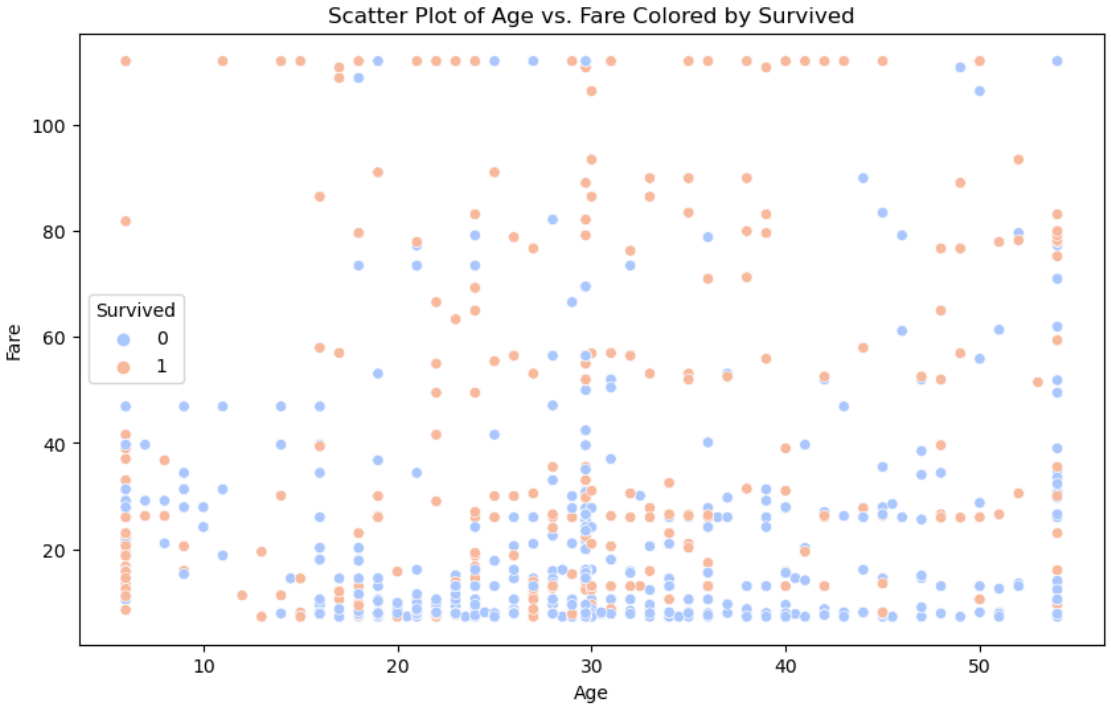
[41]:
```
sns.pairplot(df1[['Age', 'Fare', 'SibSp', 'Parch']])
plt.show()
```



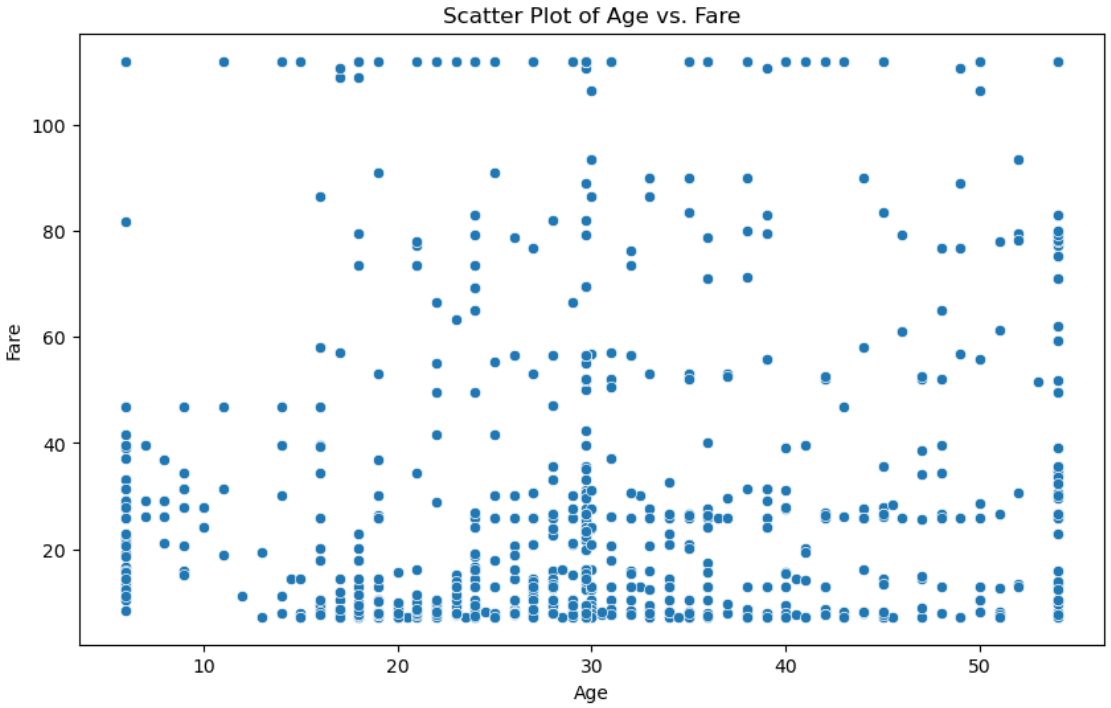
[42]:
```
plt.figure(figsize=(10, 6))
corr_matrix = df1.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



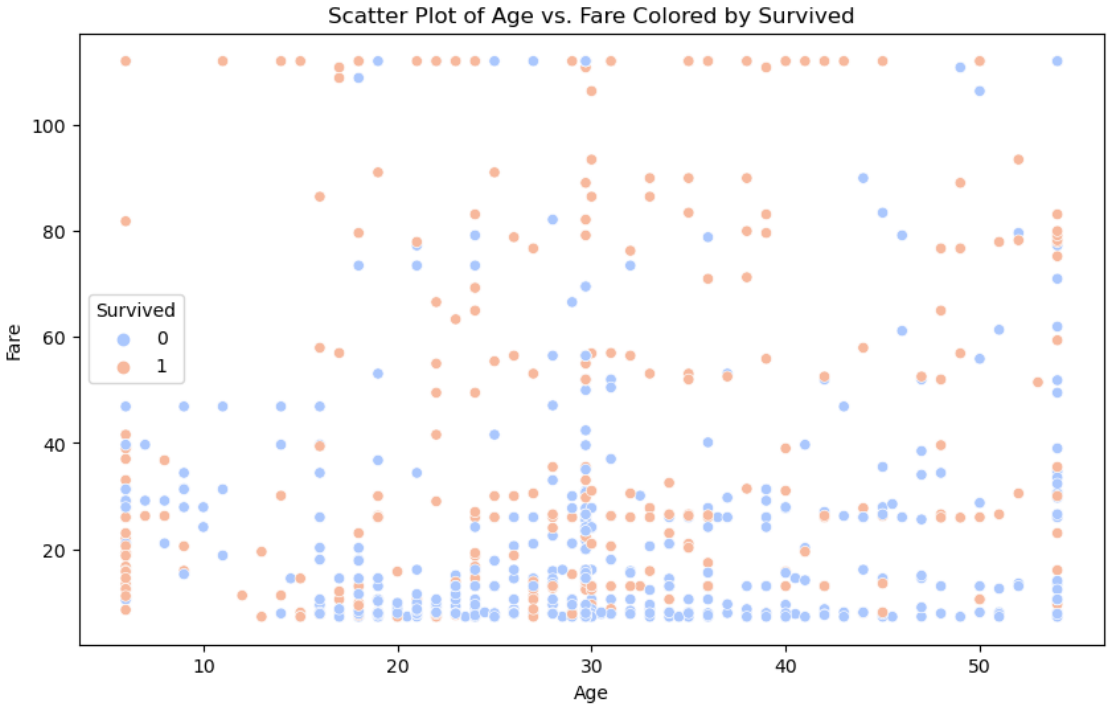
[43]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Age', y='Fare', hue='Survived', data=df1, palette='coolwarm')
plt.title('Scatter Plot of Age vs. Fare Colored by Survived')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.show()
```



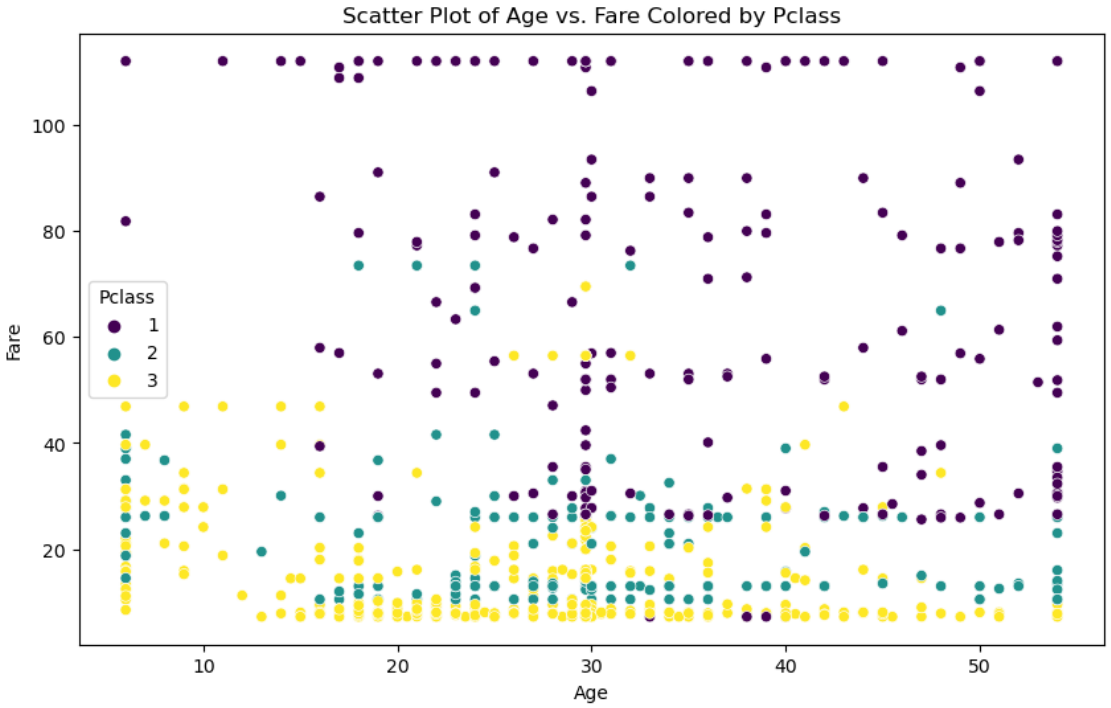
[44]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Age', y='Fare', data=df1)
plt.title('Scatter Plot of Age vs. Fare')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.show()
```



[45]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Age', y='Fare', hue='Survived', data=df1, palette='coolwarm')
plt.title('Scatter Plot of Age vs. Fare Colored by Survived')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.show()
```



[46]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Age', y='Fare', hue='Pclass', data=df1, palette='viridis')
plt.title('Scatter Plot of Age vs. Fare Colored by Pclass')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.show()
```



[47]:
```
fig, axs = plt.subplots(3, 2, figsize=(15, 18))

sns.regplot(x='Age', y='Fare', data=df, ax=axs[0, 0])
axs[0, 0].set_title('Linear Regression Plot of Age vs. Fare')

sns.scatterplot(x='Age', y='Fare', hue='Survived', data=df, palette='coolwarm',␣
 ↪ax=axs[0, 1])
sns.regplot(x='Age', y='Fare', data=df, scatter=False, ax=axs[0, 1])
axs[0, 1].set_title('Linear Regression Plot of Age vs. Fare with Hue by␣
 ↪Survived')

sns.scatterplot(x='Age', y='Fare', hue='Pclass', data=df, palette='viridis',␣
 ↪ax=axs[1, 0])
sns.regplot(x='Age', y='Fare', data=df, scatter=False, ax=axs[1, 0])
axs[1, 0].set_title('Linear Regression Plot of Age vs. Fare with Hue by Pclass')

sns.regplot(x='Age', y='SibSp', data=df, ax=axs[1, 1])
axs[1, 1].set_title('Linear Regression Plot of Age vs. SibSp')

sns.regplot(x='Age', y='Parch', data=df, ax=axs[2, 0])
axs[2, 0].set_title('Linear Regression Plot of Age vs. Parch')

axs[2, 1].axis('off')
```

```
plt.tight_layout()
plt.show()
```

[ ]:

[48]:
```
x = df1.drop(['Survived'], axis=1)
y = df1['Survived']
```

[49]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[50]:
```
x_train.shape
```

[50]: (712, 8)

[51]:
```
x_test.shape
```

[51]: (179, 8)

[52]:
```
scaler = StandardScaler()
```

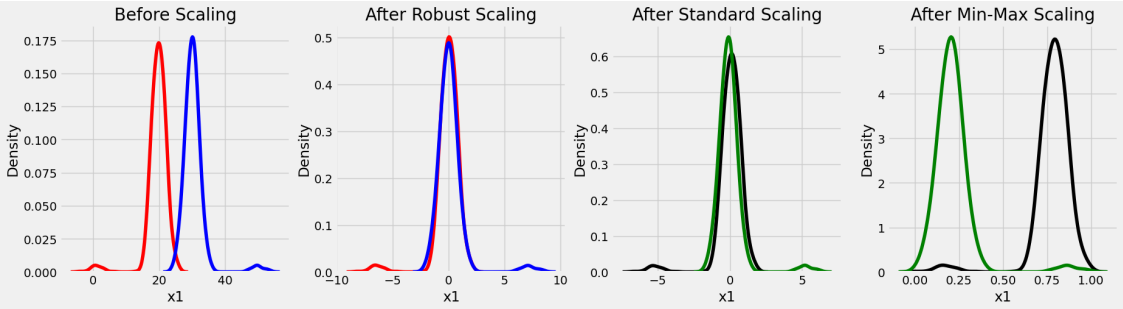
[53]:
```
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)
```

[54]:
```
x_train_scaled_df = pd.DataFrame(x_train_scaled, columns=x_train.columns)
x_test_scaled_df = pd.DataFrame(x_test_scaled, columns=x_test.columns)
```

[55]:
```
train_scaled = pd.concat([x_train_scaled_df, y_train.reset_index(drop=True)],␣
↪axis=1)
test_scaled = pd.concat([x_test_scaled_df, y_test.reset_index(drop=True)],␣
↪axis=1)
```

[56]:
```
from sklearn import preprocessing
import matplotlib
import matplotlib.pyplot as plt

%matplotlib inline
matplotlib.style.use('fivethirtyeight')
# data
x = pd.DataFrame({
    # Distribution with lower outliers
    'x1': np.concatenate([np.random.normal(20, 2, 1000), np.random.normal(1, 2,␣
↪25)]),
    # Distribution with higher outliers
    'x2': np.concatenate([np.random.normal(30, 2, 1000), np.random.normal(50,␣
↪2, 25)]),
})
np.random.normal

scaler = preprocessing.RobustScaler()
robust_df = scaler.fit_transform(x)
robust_df = pd.DataFrame(robust_df, columns =['x1', 'x2'])
```

```
scaler = preprocessing.StandardScaler()
standard_df = scaler.fit_transform(x)
standard_df = pd.DataFrame(standard_df, columns =['x1', 'x2'])

scaler = preprocessing.MinMaxScaler()
minmax_df = scaler.fit_transform(x)
minmax_df = pd.DataFrame(minmax_df, columns =['x1', 'x2'])

fig, (ax1, ax2, ax3, ax4) = plt.subplots(ncols = 4, figsize =(20, 5))
ax1.set_title('Before Scaling')

sns.kdeplot(x['x1'], ax = ax1, color ='r')
sns.kdeplot(x['x2'], ax = ax1, color ='b')
ax2.set_title('After Robust Scaling')

sns.kdeplot(robust_df['x1'], ax = ax2, color ='red')
sns.kdeplot(robust_df['x2'], ax = ax2, color ='blue')
ax3.set_title('After Standard Scaling')

sns.kdeplot(standard_df['x1'], ax = ax3, color ='black')
sns.kdeplot(standard_df['x2'], ax = ax3, color ='g')
ax4.set_title('After Min-Max Scaling')

sns.kdeplot(minmax_df['x1'], ax = ax4, color ='black')
sns.kdeplot(minmax_df['x2'], ax = ax4, color ='g')
plt.show()
```



[57]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error , r2_score
lr = LinearRegression()
lr.fit(x_train,y_train)
y_predict = lr.predict(x_test)
R2score = r2_score( y_test , y_predict )*100
print('The R2score for Linear Regression is ' , R2score)
```

```
The R2score for Linear Regression is  43.496043988962654
```

[58]:
```
from sklearn.tree import DecisionTreeRegressor
# Instantiate model with 1000 decision trees

dt = DecisionTreeRegressor()
# Train the model on training data
dt.fit(x_train, y_train);
y_predict = dt.predict(x_test)
print('The R2score for Decision Tree Regressor is ' , r2_score( y_test ,␣
 ↪y_predict ))
```

```
The R2score for Decision Tree Regressor is  -0.15186615186615193
```

[59]:
```
from sklearn.ensemble import RandomForestRegressor
# Instantiate model with 1000 decision trees

rf = RandomForestRegressor(n_estimators = 1000, random_state = 42)
# Train the model on training data
rf.fit(x_train, y_train);
y_predict = rf.predict(x_test)
print('The R2score for Random Forest Regressor is ' , r2_score( y_test ,␣
 ↪y_predict ))
```

```
The R2score for Random Forest Regressor is  0.4252145743886744
```

[60]:
```
featureImportance = pd.Series(rf.feature_importances_ , index = x_train.
 ↪columns).sort_values(ascending = True)
featureImportance
```

[60]:
```
Parch          0.012892
Embarked       0.024797
SibSp          0.042184
Pclass         0.101319
Age            0.148472
Fare           0.168210
PassengerId    0.208006
Sex            0.294120
dtype: float64
```

[61]:
```
df_x_train = x_train[ ['Pclass', 'Age', 'Fare']]
df_x_test = x_test[ ['Pclass', 'Age', 'Fare']]
rf_improved = RandomForestRegressor(n_estimators = 1000, random_state = 42)
# Train the model on training data
rf_improved.fit(df_x_train, y_train);
y_predict = rf_improved.predict(df_x_test)

R2score = r2_score( y_test , y_predict )
```

```
print('The R2score for Random Forest Regressor is ' , (R2score*100))
```

```
The R2score for Random Forest Regressor is  15.083418475481148
```

[62]:
```
from sklearn.tree import DecisionTreeRegressor,DecisionTreeClassifier
dt = DecisionTreeRegressor(random_state = 42)
# Train the model on training data
dt.fit(x_train, y_train);
y_predict = dt.predict(x_test)

R2score = r2_score( y_test , y_predict )
print('The R2score for Decision tree Regressor is ' , (R2score *100))
```

```
The R2score for Decision tree Regressor is  -5.9716859716859805
```

[63]:
```
from sklearn.svm import SVR
svr_rbf = SVR(kernel='rbf', C=1e3, gamma=0.1)

y_rbf = svr_rbf.fit(x_train, y_train).predict(x_test)

R2score_rbf = r2_score( y_test , y_rbf )
print('The R2score for RBF is ' , R2score_rbf )
```

```
The R2score for RBF is  0.046543535936969915
```

[64]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report
```

[65]:
```
logreg = LogisticRegression(max_iter=1000)
logreg.fit(x_train, y_train)
```

[65]:
```
LogisticRegression(max_iter=1000)
```

[66]:
```
y_predict = logreg.predict(x_test)
accuracy = accuracy_score(y_test, y_predict)
print('Accuracy of Logistic Regression model:', accuracy * 100)
```

```
Accuracy of Logistic Regression model: 79.88826815642457
```

[67]:
```
conf_matrix = confusion_matrix(y_test, y_predict)
print('Confusion Matrix:')
print(conf_matrix)
```

```
Confusion Matrix:
[[88 17]
 [19 55]]
```

[68]:
```
class_report = classification_report(y_test, y_predict)
print('Classification Report:')
print(class_report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.84      0.83       105
           1       0.76      0.74      0.75        74

    accuracy                           0.80       179
   macro avg       0.79      0.79      0.79       179
weighted avg       0.80      0.80      0.80       179
```

[69]:
```
from sklearn.metrics import roc_auc_score, roc_curve, auc
logreg.fit(x_train, y_train)
```

[69]:
```
LogisticRegression(max_iter=1000)
```

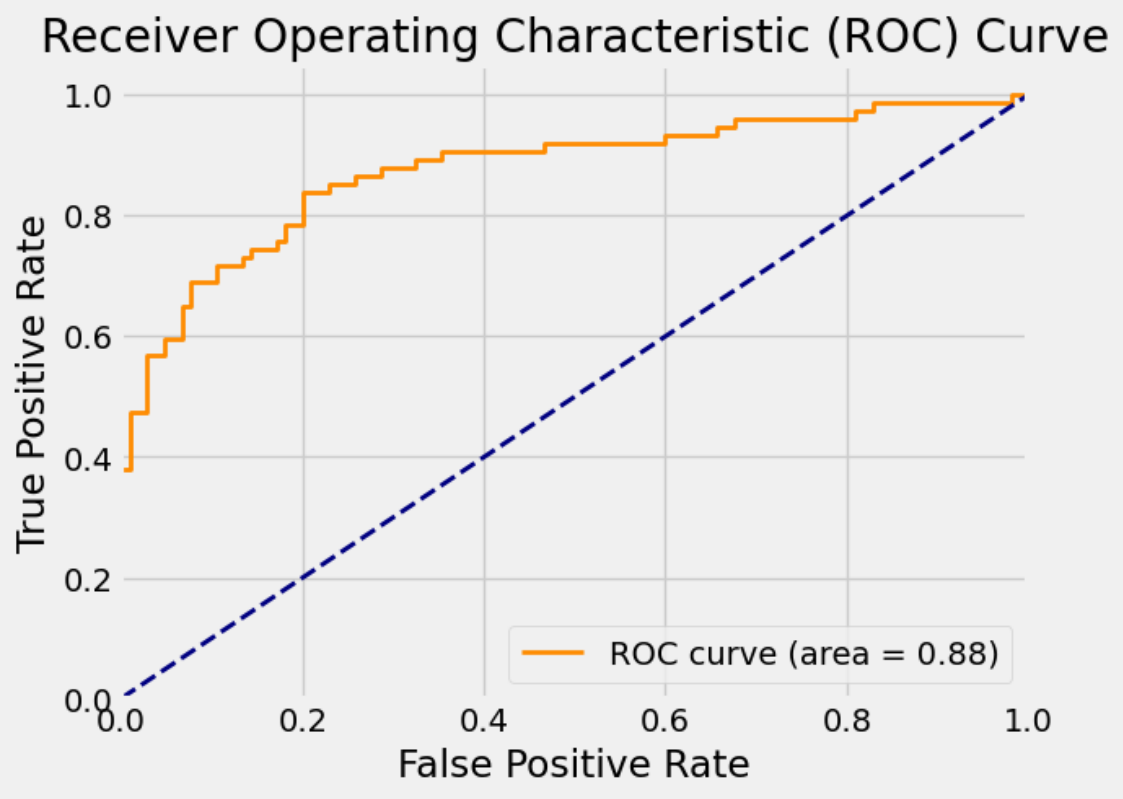
[70]:
```
y_pred_proba = logreg.predict_proba(x_test)[:, 1]
```

[71]:
```
roc_auc = roc_auc_score(y_test, y_pred_proba)
print('ROC AUC score:', roc_auc)
```

```
ROC AUC score: 0.8764478764478765
```

[72]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
```

[73]:
```
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' %␣
↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
ROC curve (area = 0.88)
0.0
0.2
0.4
0.6
0.8
1.0

[74]:

[ ]:

[ ]: